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ABSTRACT

The application of recent advances in the understanding of problem solving to the classroom is reviewed. Current research findings are described, and the instructional validity of these findings is illustrated by a research study of an instructional strategy called novice knowledge engineering. How various instructional strategies serve as knowledge refining agents is shown. Results with six freshmen honors students in college physics are presented. The students who constructed a knowledge base on projectile motion showed that little structuring via differentiation and integration had taken place prior to the knowledge base construction. The acquisition of problem-solving skill through the simultaneous refinement of declarative and procedural knowledge is illustrated, using examples from the best student in the sample. The process of constructing a knowledge base was a viable instructional strategy for refining knowledge while teaching domain specific problem solving. This strategy was a practical application of new research findings. (SLD)

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Linking recent research in cognitive science and problem solving to instructional practice: New possibilities

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Linking recent research in cognitive science and problem solving to instructional practice: New possibilities

1. Introduction

Coping with the information age means that our students must not only use computer technology, but they must also be able to gather, synthesize, and analyze information on an unprecedented new scale, to make informed decisions that are increasingly complex and multidisciplinary, and to adapt creatively to a changing world. While the number of years of schooling have stayed static, the amount and complexity of new content demands serious attention to curriculum and instruction.

Instruction in most subject areas attempts to impart not only domain-specific knowledge, but also domain-specific problem solving skill. Research to date has failed to clearly identify either the cognitive mechanisms or the pedagogical approaches that cultivate problem-solving skill within contexts, let alone transfer to other contexts (Black, Swan, & Schwartz, 1988). Unfortunately problem-solving skill and knowledge acquisition are often divorced in instruction, with the result that schooling emphasizes only the initial acquisition, and not the vital refinement of knowledge during application. Most teachers mistakenly believe that students acquire problem-solving skill by observing good problem solvers, and working many problems. Teaching rules has also proven to be of limited success if students are not simultaneously taught when and why to use certain rules -- the so-called utility and applicability conditions that connect factual and procedural knowledge in memory (Lewis & Anderson, 1985). Even if the actions of the productions needed to solve problems in the domain are laid out systematically, they are not securely connected with the conditions that should evoke them (Simon, 1979).

In problem solving, declarative knowledge ("that", consisting of facts, concepts, and principles) is needed to formulate an adequate problem representation, while procedural knowledge ("how to", consisting of rules, algorithms, and procedures) is needed to execute appropriate problem-solving actions. Instruction typically emphasizes either declarative or procedural knowledge, but seldom aims at integrating the two in a way that emulates real scientific thinking (Winograd & Hare, in press). Cues inherent in the problem description (conditions and constraints) control the selective retrieval, matching and use of declarative and procedural knowledge. In textbook problems, conditions are often explicitly given through words like "assume", "neglect", and "approximately". Unfortunately, much of such conditional knowledge of when to use specific information, and why it is significant is frequently left to the student to acquire <u>incidentally</u> over time. Novice knowledge engineering as instructional strategy offers interesting insights into what students know, how they know what they know, and the interrelatedness of what they know (Bigum, 1987; Lippert, 1987a). It compels students to think systematically and productively about the intrinsic characteristics and relationships of a topic

(Trollip & Lippert, 1988), and allows one to teach students domain-specific content together with its organization, thus facilitating an explicit emphasis on conditional knowledge. The thesis for the study reported in this paper is that asking students to construct a small knowledge base with tens rather than hundreds of rules provides a formal mechanism for teaching domain-specific problem solving and simultaneous knowledge structuring. For a more detailed discussion of this instructional strategy see Trollip and Lippert (1988).

The aim of this article is to illustrate how recent advances in our understanding of problem solving can be applied in our classrooms. The next section serves to set the theoretical backdrop by highlighting current research findings, while the section following on that serves to display the instructional viability of these suggestions at the hand of results from a research study using novice engineering as the implementation mode.

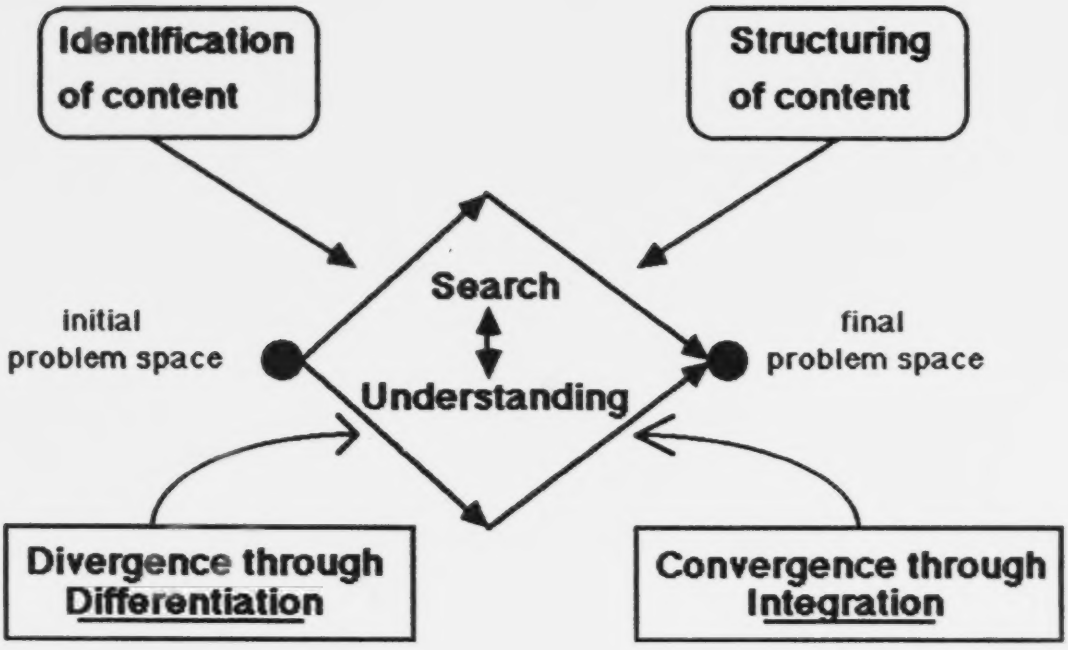
2. Refinement of knowledge: what research is saying

Refinement of knowledge in terms of its content and organization is at the heart of the schooling enterprise. This section summarizes the kinds of knowledge, refinement, stages of refinement, and instructional strategies that researchers are addressing.

Kinds of knowledge

Typically declarative knowledge is seen as propositions, while procedural knowledge is seen as productions. This dichotomy is helpful for educational purposes, but does not suffice to describe the refinement of the entire cognitive knowledge base. Recent articles have eluded to a third characterization of knowledge, namely conditional knowledge (Tennyson & Christensen, 1988), functional knowledge (Greeno, 1987; Greeno & Berger, 1987), or control knowledge (Reif, 1987). The general notion is that knowledge of applicability conditions, and consequences of actions ("when, where, and why") is crucial in the development of a coherent, interpretable and useful knowledge base. As such it is a set of propositions that states the conditions under which particular components of declarative and procedural knowledge are applicable to a given task. Therefore conditional knowledge acts as selective retrieval, matching and refining agent, as illustrated below.

The figure shows that during initial problem representation conditional knowledge is responsible for retrieving and matching the relevant declarative and procedural knowledge. If problem solving is unsuccessful, it could be due to errors in using the selected formulations (eg. arithmetic errors, errors in manipulating the equation(s), etc.). Checking of a different nature occurs when the student realizes that the initial representation of the problem is incorrect or incomplete, and solicits new conditional knowledge. Rethinking what the relevant issues are results in a change in the declarative and procedural knowledge selection.



- compare and contrast (distinctiveness)
- analyze for attributes and consequences
- conceptual synthesis through
  - exploration
  - elaboration
  - explanation
  - interpretation
  - extraction
- evaluation of meaning

- compare and contast (compatibility)
- procedural synthesis through
  - expansion/contraction of conditions
  - reformulation of representation
  - restructuring of relationships
- evaluation of relationships

Figure 1: Function of conditional knowledge

Kinds of refinement

The majority of problem solving research assumes that the declarative knowledge is first encoded from text or from spoken words, then procedularized into a skill. In Anderson's skill acquisition theory (Anderson, 1987) the process of conversion is achieved by using general weak methods which can convert declarative knowledge into domain-specific procedures via compilation. The encoding of the declarative knowledge is taken to be a straightforward storing. New research results are however revising this claim (Chi, Bassok, Lewis, Reimann, & Glaser; 1987). Weak problem-solving methods like analogy can be far more effective if they operate on a rich representation of knowledge. The question is how instruction can cultivate such a presentation.

The interactive phases of knowledge engineering (acquisition, representation, searching, tuning, validation, restructuring) manifest the evolution of a conceptual structure through successive refinement of both the content and organization of knowledge. The result is generalization and specialization of content through restructuring activities such as differentiation and integration, which are generated by metacognitive knowledge and processes. See Dietrich and Michalski (1983) for a review of the AI literature, and Murphy and Medlin (1985) for a review of the psychological literature.

Differentiation implies that more specific ideas are subsumed under more general ideas and entails processes such as analysis of the attributes, function and application of concepts through exploration, elaboration, and explanation; and a conceptual synthesis through interpretation and extraction processes. Differentiation is therefore the addition of new propositions and/or problem-solving steps that provide more specific and detailed information within an existing set or procedure.

Integration must be preceded by differentiation, and describes the degree to which ideas are inter-related (West, Fensham, & Garrard, 1985). It entails processes such as evaluation of relationships and a procedural synthesis through the expansion or contraction of application conditions. Integration is therefore the addition of new and/or deletion of incorrect or irrelevant propositions that link various sets of previously existing propositions within or among schemata. In terms of procedural knowledge, integration entails the addition, deletion, and/or reordering of steps in problem-solving procedures.

The processes of differentiation and integration interact in that one serves as the catalyst for the other, as illustrated below.

As a practical example, the figure illustrates how differentiation and integration operate during the construction of a knowledge base (CKB), and which cognitive processes are activated to support the resulting refinement of the content and organization of knowledge. The figure serves as a reference frame for the reader, and not as a strictly

correct model, since the interaction of differentiation and integration, as well as the controlling influence of metacognition is not directly illustrated. What should be evident though is how the CKB process supports the theoretical notion that instruction should do more than cultivate knowledge, it should also teach the accompanying cognitive processes.

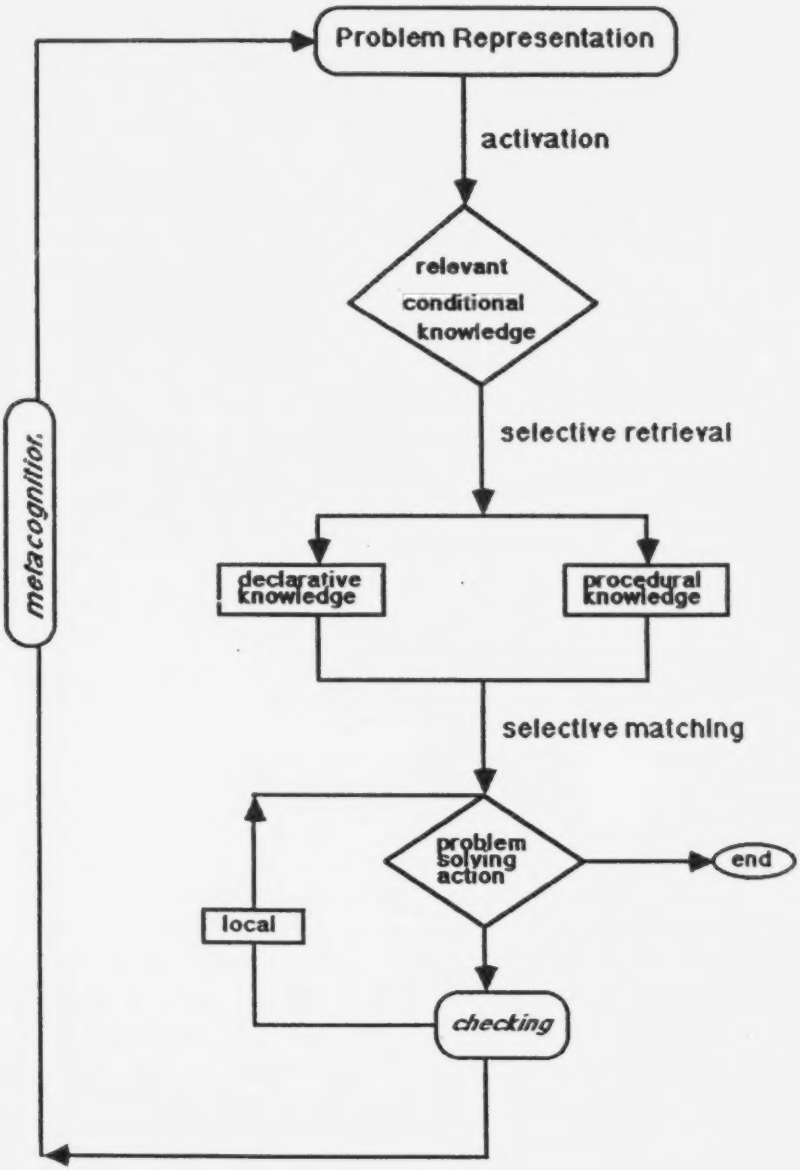


Figure 2: Cognitive processes during CKB

Stages of refinement

It is very clear from the misconceptions literature that knowledge and performance are not all or none phenomena, and that partial and incomplete knowledge may more accurately characterize students' cognitive state. The expert-novice literature has typically discussed dichotomous and therefore discrete states of cognitive performance: novice or expert (Chi, Feltovich & Glaser, 1981; Larkin, 1983). It clearly simplifies the situation to say that experts use theoretical principles (eg. energy conservation) and forward chaining, while novices depend on surface features and backward chaining. Roschelle's findings (Roschelle & Greeno, 1987) recently presented quite a different picture of expert reasoning than indicated by these studies. They found that representations of experienced subjects were strongly influenced by concrete objects in the problem, and that knowledge at various levels of abstraction can interact cumulatively in the development of an integrated representation or mental model.

Characteristics of the declarative knowledge of beginning physics students are poorly differentiated concepts, imprecise propositions and a lack of conditional knowledge (Champagne, Gunstone, & Klopfer, 1985). Good students learn with understanding: they generate many explanations which refine and expand the conditions for the action parts of example solutions, and relate these actions to principles. These self-explanations are guided by accurate monitoring of their comprehension failures and successes. Such learning results in an example-independent knowledge and in a better understanding of the principles presented (Chi et.al., 1987). Poorer students do not generate sufficient self-explanations, inaccurately monitor their learning and subsequently rely heavily on examples. Sternberg (1985) quotes the deficient cognitive functions most often encountered in novice behavior to be 1) unsystematic exploration, 2) inadequacy in experiencing and defining an actual problem, 3) restricted inferential thinking, 4) impaired strategies for hypotheses testing, and 5) inadequate communication of the outcome of elaboration. The development of expert-level processes in students thus involves effective formation of both knowledge and cognitive operations. **How should one teach knowledge in order to develop cognitive operations, and conversely, how does one teach cognitive operations in order to develop high quality knowledge and the ability to apply it accurately?**

Requirements for the acquisition of domain expertise have been laid out by Dreyfus and Dreyfus (1986). The gist of their analysis of skill acquisition is that the transition from novice to expert entails that declarative knowledge is increasingly utilized procedurally, and that with experience within a domain, knowledge of "what-to-do-in-what-situation-at-what-juncture-and-for-what- reason" is developed. It entails a progressive evolution from detached, analytical behavior that consciously decomposes an environment into recognizable elements, followed by abstract rule following, to concrete, intuitive behavior based on accumulation of new situations as similar to <u>whole</u> remembered ones. What is primarily involved in this evolution is conditional

knowledge acquisition within specific situations, and its influence on the relationships between declarative and procedural knowledge.

They acknowledge a smooth transition between five distinguishable stages, namely novice, advanced beginner, competent, proficient, and expert. Definitive of both the novice and advanced beginner stage is behavior that recognizes learned features and applies learned rules slowly and with conscious choices of goals and decisions after reflection of alternatives. The more expert-like stages are reached when procedures and organizational plans are no longer purely objective and certain constellations of elements call for certain conclusions or expectations to be investigated, since memory triggers plans that worked in the past. Intuition becomes the product of situational involvement. Some analytical thinking and rule application lingers, while recognition of similarity in terms of organization and understanding becomes prevalent. Expert-like performance is further characterized by generativity, a great deal of episodic (context-dependent) and functional knowledge (knowledge of relationships), and awareness of progress on problems.

With reference to a given domain, the transition features described above are obviously of a longterm nature. However, learners within a particular level can display behavior that can be identified as typically novice, or competent, etcetera, for the given task and domain at hand. Additional evidences of a slow, mediated transition from novice to expert in our study were found in a 1) decline in errors, 2) decline in time on task, 3) change in problem and physics representations, 4) refinement of procedural knowledge seen in pattern recognition and action-sequencing, 5) development of conditional knowledge, 6) conceptual elaboration, and 7) curtailment of reasoning (issues of efficiency, conciseness, and a shift from quantitative to qualitative reasoning).

Kinds of instructional strategies for refinement of knowledge

Current research reports indicate how various instructional strategies serve as knowledge refining agents. Thinking-aloud problem solving makes students more aware of their thinking, more accurate in spelling out relationships and interpreting information, while giving great insights into how students store, recall, and use their knowledge (Champagne, Gunstone, & Klopfer, 1985; Chi, et.al., 1987). Reif (1987) suggests concept learning by procedural interpretation and diagnosis. Educational technology in the form of intelligent tutoring systems and microworlds creates enhanced learning environments, but these are expensive and mostly still in the research phase (Wenger, 1987; White & Frederiksen, 1987). In contrast to these AI applications, though within the same paradigm, we decided to explore the efficacy of expert systems as a teaching tool because many commercial systems offer demo disks at prices affordable by most teachers (Lippert, 1987b). This, coupled with the observation from literature that novices become para-experts as a result of knowledge engineering, provided the rationale

for this study. We used an in-house expert system shell written in Turbo-Pascal (Smith, Starfield & Macneal; 1985) that interfaces with any wordprocessing editor capable of creating ASCII files. The students' tasks were to create questions, decisions, rules, and explanations to describe classical projectile motion. As such the construction of a knowledge base provided a context for knowledge refinement through differentiation and integration. The evolutionary changes could be seen by tracing students progress from the pretest through the construction of the knowledge base on paper and on the computer, to the posttest.

From a pilot study and observations from literature we argued that the CKB process aids comprehensive refinement of domain-specific knowledge due to greater degrees of elaboration during encoding, greater quantity of material processed in an explicit, coherent context, and therefore in greater semantic depth. Students are taught a thinking/learning strategy that forces systematic exploration, planning, and evaluation. Since relationships, rather than loose facts are stressed, they are taught the value of reconstruction and design, rather than rote, detailed recall from memory. This should positively effect transfer potential.

3. Implementation of the summarized research suggestions

The aim of the qualitative study we undertook was to explore the knowledge refinement effects of the CKB process as a possible new teaching method. In particular we were interested to see how the different kinds of knowledge would be effected, what transitions in skill acquisition we would see, and what the nature of the refinements would be in terms of content and organization. We selected a representative sample of six freshmen honors students in physics. After their formal instruction in projectile motion and practice in knowledge engineering, they individually built a knowledge base on projectile motion. Concurrent thinking-aloud protocols were recorded on audio- and videotape. See Lippert and Finley (1988) for a more detailed account of the study. Since each student was observed over the course of 30 hours (including pretesting, posttesting, and a debriefing interview), the amount of data is formidable. We have selected only a small fraction of it to highlight the implmentation of some of the theoretical research suggestions summarized above.

Students spent from 16 to 23 hours coming up with a knowledge base ranging from 13 to 33 rules, 7 to 19 questions, and 13 to 28 decisions, but the knowledge bases were still not representative of what they knew, as elicited during the pretest. Although all students reported an integration of their knowledge, and explicit awareness of the strategic value of conditional knowledge, this integration and differentiation occurred only at the hand of laborious elaboration. All students had far more difficulty structuring their knowledge, than coming up with sufficient content for the knowledge base, since aspects that they had learned rotely and did not understand, and therefore could not work with, soon became evident to them. This resulted in

self-evaluation of the extent, accuracy, and adequacy of their knowledge. Students that were more successful developed questions, decisions, and rules in parallel, and isolated the key concepts for differentiation and integration early on in the task, thereby ensuring coherency and confinement of the problem space to a manageable size.

Features of the problem-solving activities gathered from the verbal protocols were in agreement with findings by Chi et.al. (1987) who found that good students:

1) Produced a greater number of explanations which consisted mainly of justifications for inferences about conditions, consequences, and goals.
2) Achieved greater success since instantiations of the weak methods depends on the representations of their declarative knowledge, which was more complete and correct.

With regard to domain-specific problem solving, students that built knowledge bases that incorporated procedures and equations germane to projectile motion problems, showed an improvement in their problem solving on the posttest. Those that confined themselves to a more qualitative knowledge base showed no improvement. These themes, together with the acquisition of problem-solving skill through the simultaneous refinement of declarative and procedural knowledge will now be illustrated at the hand of some examples from the refinement highlights of the best student in the sample, named Peter.

In terms of Dreyfus and Dreyfus's scheme Peter functioned at a proficient level for his peer group, but as a novice in comparison to real experts. On the pretest he couldn't solve equations that involved the calculation of angles, nor was he aware of specialized formulas he should have known, eg. the range equation and the fact that at maximum range the angle is 45 degrees. A particular problem occurred several times, namely when angle, velocity, and time had to be found as a function of each other. He was also prone to solve problems by listing the given values and possible formulas, then plugging the values into the formulas and using mathematical manipulation to come to an answer.

However, it was characteristic of Peter to consider concepts, relations, and methods not mentioned in the problem statement. He was able to come up with an appropriate problem representation by extracting information that real novices overlooked eg.: "5000km! That's a fourth around the world. This is almost circular motion. At that distance the world is curved." He perceived structure and relationships amongst concepts functionally and often articulated explicit application conditions that were attached to his procedural knowledge. For example, asked to predict the trajectory that a missile will follow as it moves from the North Pole to the equator, he immediately asked "Where is the observer?" thereby expressing knowledge that the location of the observer determines the observation. His physical intuition was well developed too so that he anticipated and evaluated outcomes without much conscious deliberations. For

example, "That's a heck of a cannon! The speed of those shells is faster than sound. They'll hear them coming for sure!", or, "Seems about right for a plane", or "It seemed pretty silly that he could throw it farther up than horizontal.", or "Hitting a target 5000km away would never happen first time in the real world, because they know there are variations in the air density and weather systems. So essentially they have missiles that adjust automatically for that." In the debriefing interview he said: "The structure of the inference engine forced me to approach the problem with a more formal, and logical strategy which I don't find natural and honestly don't use. I tend to run by intuition."

Evidences of knowledge refinement on the posttest

A general trend toward more conciseness reduced the overall time on task. This can be largely attributed to the abandonment of the pretest strategy of listing variables, writing down of appropriate equations and then plugging in known values. The preference became to identify the problem type and its associated features, and writing of an equation that immediately contained the dimensions of the problem (characteristic of the forward chaining approaches of experts), eg. $-730 = -5(5^2) - 5vy$. Use of specialized formulas such as $y = .5at^2$ instead of the longer and more general equation of $y = .5at^2 + v0t + y0$ effectively eliminated some unnecessary steps (curtailment of reasoning). This can also be seen as a development of efficiency through pattern recognition as entire subgoals and actions are deleted. For example:

Question #	PRETEST	POSTTEST
4 (goals)	Find maximum velocity Find angle Find initial velocity Find maximum height	Find initial velocity Find maximum height
5 (actions)	A1: vx=15m/s, h=100m A2: $y = -10/2t^2 + y0$ A3: $-100 = -5t^2$ A4: $t = 20s$ A5: $x = 15x\ 20$ m	$100-5t^2$ $t=4.5s$ $d = 15x4.5 = 67.5m$

This can be attributed to a differentiation amongst variables in given situations, leading to a better conceptual integration of the function of the various entities.

Development of conditional knowledge became evident through many new associations. For example, referencing some of the key constructs of his knowledge base, namely "If you want to optimize the shelling, then change the velocity first, because the angle is related to the distance it flies, to the sine of the angle which increases slower than the velocity, and you'd have to change the angle quite a bit in order to get an equivalent response to changing the velocity. Initial vertical

position is another factor, though it would affect the distance less than the angle since it doesn't influence time which is quadratic in the y-equation and disappears in the equation for maximum height."; or, "The first thing is to find out whether gravity is constant. It makes the solution a lot harder if it isn't. I'd say range must be less than 100 miles for gravity to be constant."

Instances of refinement during CKB

The product of the CKB process alone indicated refinement of knowledge that could not have occurred at the hand of contrived textbook problems, because inference of important functional relations does not necessarily occur when students learn procedures in the absence of functional knowledge (Greeno & Berger, 1987). The refinements indicated that a relational framework had been developed that was neither articulated on the pretest or had been taught during the prior instruction. Peter had the fewest questions (and therefore variety of input) of all the subjects. Yet he had the most versatile and well integrated knowledge base of them all, because he was strategic in isolating the key descriptive concepts of projectile motion and then differentiating these into instantations of several projectile phenomena. He developed a more compact and coherent knowledge base by refining a limited number of concepts, rather than assimilating a broad spectrum of concepts. His decisions show how he took five concepts, namely angle, time, maximum height, velocity and distance and differentiated them to 14 variations of these basic concepts. For example:

velocity -> initial, impact, vertical at impact, general vertical max
height -> from ground, from an elevation
angle -> positive projection, negative projection, impact
time -> general, 0 at max height, v0sin@/g at max height
distance -> to max height, to target

The most obvious refinement event is the new connections he made between velocity and projection angle. On the pretest he judged angle and initial velocity to be independent and drew a horizontal line. By the time he was posttested he had refined this notion and could draw a graph wherein all points were possible (a grid), showing that any angle can be accompanied by any initial velocity and that one variable did not determine the other. During CKB his refinement progressed from "I have to change the 'decrease and increase angles' to 'move it closer to or further away from 45 degrees because either way you increase the range'", to "Falling short ... angle is not 45 degrees ... and velocity is not the max, then move the angle closer to 45 ... let's see, I'll try to think of some other condition ... velocity is at max ... I haven't allowed for shooting it off from different altitudes, because if you're elevated, you'd increase your range, even though you're not shooting with any vertical velocity. So I have to change the idea of the angle coming from -90 to +90 degrees. I'll have to put in other angle values, positive, but not 45 or 90 ...", as illustrated below. Other main events are the integration of elevation as a new factor

determining projection (how this introduced differentiation of angle specification), consideration of impact and subsequent differentiation of velocity and distance, and differentiation of an alternate placement of the coordinate system so that time, maximum height, and horizontal distance are calculated differently.

In the account of the refinement only decisions and questions that underwent changes are listed each session. For the convenience of the reader, decisions have been rearranged to highlight clusters, which makes comparison between sessions easier. Since numbers of decisions are relabeled from session to session, no significance should be attached to them in this discussion.

Peter's decision evolution

Session 1

d1: "Time = -v0sin@ +/- [(v0sin@)^2 - 2*a*s0y] / a".

d9: "Time at maximum height = v0sin@/a".
d10: "Maximum height = 3/2[v0sin@]^2 + s0y".
d11:"Horizontal distance at maximum height=(v0^2)sin@cos@/a + s0x".

d8: "Move angle towards 45".
d4: "Move angle away from 45 and/or decrease v0".
d3: "Move angle towards 45 or increase v0".

d7: "Increase v0".

Session 2
Integration of s0y (elevation) factor causing angle differentiation

d4: "Move angle away from +45 and/or decrease v0 and/or s0y".
d3: "Move angle towards +45, increase v0 and/or s0y".
d8: "Move angle towards +45".
d5: "Move angle towards -90".

d13:"Increase v0 and/or s0y".

Session 3
Further integration of s0y factor

d11:"Increase s0y and/or move angle closer to +45".
d12:"Increase s0y".
d13:"Decrease s0y".
d14:"Decrease s0y and/or v0".
d15:"Decrease s0y and/or move angle away from +45".

d16:"Decrease v0 and/or move angle away from +45".

Session 4
Integration of distance and alternate coordinate system

```
d3: "Distance to target = v0cos@ (-v0sin@ +/-  [(v0sin@)^2 +
    2*a*(s0y)]/-a)".
d4: "Set parameters so that distance = -a(t^2)/2 + v0sin@ + s0y".

d21: "Time at maximum height is 0".
d22: "Maximum height is s0y".
d23: "Horizontal distance at maximum height is 0".

d25: "Maximum height = 3/4 [( v0sin@ )^2]/a + s0y".
```

Session 5
Differentiation of impact

```
d25: "Maximum height = 1/2 [( v0sin@ )^2]/a + s0y".

d27: "Vertical velocity at impact = -  [ (v0sin@)^2 - 2a*s0y ]".
d3:  "Velocity at impact = -  [(v0sin@)^2 - 2a*s0y + (v0cos@)^2]".
d4:  "Angle of impact = arctan(  [(v0sin@)^2 - 2a*s0y]/v0cos@)".
```

Peter's question evolution

Questions were refined simultaneously with the decisions. Observe therefore how Question 2 Session 2 shows the differentiation of angles, and how in Session 3 Question 4 from Session 1 was separated into two questions (4: issues of impact and 6: issues of maximum height) because they had previously been combined. In Session 2 Question 5 introduced the new elevation factor. In Session 4 the other new factor, distance to target, was brought in via Question 7.

Session 1

```
Q1: "Is projectile:"
a1 "Overshooting"
 2 "Hitting target"
 3 "Falling short".

Q2: "Is angle"
a1 "0"
 2 "45"
 3 "90"
 4 "Something else"


Q3: "Is velocity"
a1 "0"
 2 "At maximum"
 3 "In between".
```

Session 2

```
Q2: "Is angle:"
     a1 "0"
      2"+45"
      3 "+90"
      4 "-90"
      5 "+, not +45 or +90"
      6 "-, but not -90".
```

```
Q4: "Do you need to know:"
a1 "Time to impact"
 2 "Velocity and/or angle to impact in a given time"
 3 "Time at maximum height"
 4 "Maximum height"
 5 "Horizontal distance at maximum height"
 6 "None of the above".
```

Session 2

```
Q5: "Is launch pad's initial vertical position:"
a1 "Above ground, but not at maximum height"
 2 "At ground level"
 3 "Underground"
 4 "At maximum height".
```

Session 3

```
Q4: "Do you need to know:"
a1 "Time to impact"
 2 "Velocity and/or angle to impact in a given time"
 3 "None of the above".

Q6: "Do you need to know:"
a1 "Time at maximum height"
 2 "Maximum height"
 3 "Horizontal distance at maximum height"
 4 "None of the above".
```

Session 4

```
Q7: "Is distance to target known?"
a1 "Yes"
 2 "No".
```

Space does not allow to relate the many other instances of refinement, nor a description of how the rules evolved. Peter started the on-line phase with four questions, 12 decisions, and 12 rules. Altogether he came up with 83 new components (7 questions, 31 decisions, 45 rules). In the process of unifying his various concepts, he developed several general formulas that are not to be found in a textbook. This testifies to his generative abilities, level of comprehension, and ability to capture projectile motion in mathematical language. What is characteristic of Peter is that he used very few questions to create relatively many rules, indicative of the interconnectivity of concepts he constructed through differentiation. Complexity became a result not of mere quantity, but a combination of both the quality and quantity of relations.

In summary one can say that a refinement in his knowledge as a result of the CKB process did take place, both in the declarative and the procedural domain. He could account for the connection between angle

and initial velocity in a declarative and procedural way, and had isolated the factors that determine the outcome of that relationship. Other examples include the refinement of the concepts of time and maximum height when he introduced negative angles; or the gradual differentiation of the concept of time in flight to include time at maximum height, and time at impact. Often refinement was the direct result of deliberate attention to conditional knowledge, such as "Is projection occurring ground to ground, or are launch and target vertically displaced? This can be further supported from independent comments he made on the evaluation survey, and subsequent interview. (R: Renate, P: Peter)

R: Describe to me how you would have learned projectile motion if you hadn't built a knowledge base.

P: I'd just have an equation memorized, like I basically do for angular motion problems. If it comes out, I don't know if it's right or not. But by working with the things there, you have a better idea of what's reasonable. I would probably never even have a second thought about what the angle has to do with the velocity, or what any of that has to do with the time it takes to hit a certain point in the trajectory.

R: So you wouldn't have made those connections, those relationships?

P: Not unless I was forced to for some reason, and then that would go in one ear and out the other. You either have to learn everything from it by spending a lot of time on it or spend a little time on it and not really do anything with it. What I learned about projectile motion was that some of the interrelationships of variables within the projectile motion equations, affect the result more than others, and therefore are more important. It'd be, like, the angle versus velocity, which one would change, would affect the ... outcome more. Velocity is more important than the angle. An angle is more important than initial height.

R: What kind of problems can you solve now that you wouldn't have been able to do before?

P: Those with multiple unknowns, tying, say, different equations together, tying together different ideas. But my organization still stinks. I can do, say, one, or two, or three at a time. I can't see the whole picture all, all at once.

R: How did you feel about the problems now on the posttest versus on the pretest?

P: I think I could do 'em faster. It took a lot less time and I think I was more accurate in doing 'em.

R: And what do you ascribe it to?

P: It just seems to be easier to visualize what's going on. I could even draw out those pictures of how the angle affects, say, the distance and the time. And I can do that for all the variables. So you just get this idea of how if one variable changes, how the rest of them will change. The interrelatedness of the things.

In summary, it was encouraging to see that even the "best" student in the study showed considerable refinement of knowledge, despite the fact that his knowledge base was by far not representative of what he knows (though representative of what he can quantizise). That a student with such a good initial conceptual framework nevertheless benefits from this instructional method, but needs 16 hours to complete a knowledge base of the discussed size, illustrates that the process of knowledge refinement is not a trivial matter at any level of cognitive complexity.

4. Summary

Students in this study displayed a wealth of declarative information (after all, they were honors students). In the face of structuring it into a coherent unit through procedularization, they displayed however that very little structuring via differentiation and integration had taken place prior to CKB. Formal instruction in the regular physics classroom had not helped them develop the functional or conditional knowledge that is critical for the adequate interpretation and application of knowledge in new situations. And when conditional knowledge is insufficient for solving a problem, the search for a plan using methods and equations fails.

The time to develop a knowledge base that would truly reflect Peter's entire knowledge in the domain of projectile motion would have exceeded 50 hours, which is obviously prohibitive. It however illustrates the point that problem-solving skill acquisition is a slow process, because the construction of meaningful interrelationships between a large number of factors suffers from combinatorial explosion. It is then no wonder that true expertise in a domain takes years to acquire. A more important observation though is the fact that the instructional implications of these findings call for a substantially different type of instruction -- an instruction that can successfully escalate skill acquisition by mediating experiences that allow students to elaborate their knowledge in order to integrate and differentiate it. It has been too long that students have been allowed to be passive recipients of knowledge that they do not understand. In this study, understanding knowledge that was already "known", constituted significant learning. The function of students' explanations during CKB seemed to have been both the enhancement of their initial understanding and generation of new understanding.

We were satisfied that the CKB process is indeed a viable instructional strategy to comprehensively refine the three kinds of knowledge while simultaneously teaching domain-specific problem solving. An area not discussed in this paper, though very well represented in the data, is that of metacognition and the development of cognitive strategies. Good students were more prone to monitor their comprehension and progress, and better able to diagnose their errors with specific inquiries. The fact that students actually see their own cognitive "knowledge base" in operation during CKB is an advantage that this

learning strategy offers. This was the verdict about the benefit of the knowledge engineering experience by the students involved.

4. Conclusion

Many mistakes exhibited by students are traceable to knowledge that is fragmented and uninterpretable. Elaborations during CKB revealed students' understanding by showing whether or not they knew 1) the applicability conditions of actions, 2) the consequences of actions, 3) the relationship of actions to goals, and 4) the relationship of goals and actions to natural laws and principles. Elaboration is a mechanism that allows students to develop cognitive processes to explain, infer, and explicate the conditions and consequences of procedures so that knowledge structuring can occur.

The CKB exercise demands solving a novel and ill-structured problem. While routine problems are solved by applying a known procedure, nonroutine problems require generation of new functional knowledge because new operators have to be constructed to make the problem solvable (Greeno & Berger, 1987). Woodley and Driscoll (1977) describe the process of generating alternatives as constructing new relationships, integrating ideas within a new frame of reference, or seeing new possibilities in the given information. Our data reflects these observations.

The themes touched upon in this study also blend with current work by Greeno, Reif, Chi and others on the role of problem types and generative processes in problem representations as an extension of the work by Gestalt psychologist such as Duncker and Wertheimer. The data supports Larkin and Simon's (1987) conjecture that "students may well be unable to solve problems in part because they learn principles, and do not translate them into inference rules" (p. 75), and Champagne's (1987) statement that domain-specific problem solving is inevitably a restructuring of knowledge within the domain. Studies of this nature can help researchers understand the thought processes that underlie effective student learning and then to translate these findings into improved teaching practices. Findings can contribute to the refinement of cognitive learning theories by clarifying processes by which complete structures of knowledge are acquired and modified.

As instructional strategy CKB is a practical application of new technology and an integration of various research themes. As a teaching strategy, it blends the acquisition of knowledge and an experience base, with the nurture of the higher-order thinking skills. It is a new process to trace changes in cognitive structure due to instruction, allows for individualization as well as cooperative learning, and promises to be effective in dealing with misconceptions (Lippert, 1987c). It is also a promising testing procedure to replace traditional tests that are insensitive to structure, errors of omission and intrusions. Finally, it has the potential to increase fundamental understanding of learning, and to yield new views of teaching and curriculum goals.

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